Prediction and Classification of Neonatal Jaundice using Multi Layer Perceptron Based System

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Abstract—**Jaundice is the most common and one of the most vexing problems that can occur in the newborn. Although most jaundiced infants are otherwise perfectly healthy, they make us anxious because bilirubin is potentially toxic to the central nervous system and, if the serum bilirubin level is very high, kernicterus (bilirubin encephalopathy) can occur [2].**

The idea of predicting risk of neonatal jaundice before and after delivery is tried in this paper. For this purpose multi layer perceptron (MLP) neural network is used for prediction of neonatal jaundice before and just after delivery (in first 24 hours) and also classification of jaundice into physiologic and pathologic jaundice types. A total of 552 medical records were collected from newborns in Iran. To evaluate results of these models we used performance evaluation matrix criteria, which include percentage of accuracy (correct classification) (CC%), sensitivity (SE%), and specifity (SP%). The above mentioned criteria for jaundice prediction before delivery were approximately 71%, 82%, 61%, while for jaundice prediction after delivery were 81%, 91%, 73%, respectively. These results show that the proposed MLP based systems can achieve satisfying results for predicting risk of jaundice considering this fact that physicians do not have any estimation about probability of jaundice appearance. Also we achieved a very good result for jaundice type classification (95%, 96% and 94% for accuracy, sensitivity and specifity, respectively).

Keywords: Multi Layer Perceptron Neural Network, Neonatal Jaundice Prediction, Classification, Physiologic, Pathologic

I. INTRODUCTION

Jaundice is a common and, in most cases, benign problem in neonates. In 1990s jaundice was the prevalent cause of returning of newborns to hospitals. So, early diagnosis of newborns liable to jaundice is important [1]. Nonetheless, untreated, severe indirect hyperbilirubinemia is potentially neurotoxic. Jaundice is observed during the first week of life in approximately 60% of term infants and 80% of preterm infants [2].

Jaundice usually begins on the face and then progresses to the abdomen and then the feet. Jaundice resulting from deposition of indirect bilirubin in the skin tends to appear bright yellow or orange.

Low-risk jaundiced infants who are full term and asymptomatic may be evaluated by monitoring serum total bilirubin levels. Regardless of the gestational age or time of appearance of jaundice, those with significant hyperbilirubinemia and all patients with symptoms or signs require a complete diagnostic evaluation, which should include determination of the direct and indirect bilirubin fractions, hemoglobin, reticulocyte count, and blood type, a Coombs test, and examination of a peripheral blood smear [3].

Under normal circumstances, the level of indirect bilirubin in umbilical cord serum is 1-3 mg/dL and rises at a rate of less than 5 mg/dL/24 hr; thus, jaundice becomes visible on the 2nd-3rd day, usually peaking between the 2nd and 4th days at 5-6 mg/dL and decreasing to below 2 mg/dL between the 5th and 7th days of life. Jaundice associated with these changes is designated "physiologic" and is believed to be the result of increased bilirubin production after the breakdown of fetal red blood cells combined with transient limitation in the conjugation of bilirubin by the liver.

Prediction of which neonatal infants are at risk for exaggerated physiologic jaundice can be based on hour-specific bilirubin levels in the 1st 24-72 hr of life [3].

The diagnosis of physiologic jaundice in term or preterm infants can be established only by precluding known cause of jaundice on the basis of the history and clinical and laboratory findings**.** In general, a search to determine the cause of jaundice should he made if (1) it appears in the first 24-36 hour of life, (2) serum bilirubin is rising at a rate faster than 5 mg/dL/24 hour, (3) serum bilirubin is greater than 12 mg/dl, in full-term (especially in the absence of risk factors) or 10-14 mg/dL in preterm infants, (4) jaundice persists after 10-14 days of life, or (5) direct-reacting bilirubin is greater than 2 mg /d L at any lime. Among other factors suggesting a nonphysiologic cause of jaundice are family histories of hemolytic disease, pallor, hepatomegaly, splenomegaly, failure of phototherapy to lower bilirubin [3].

II. LITERATURE STUDY

A. Review Stage

Lee et al proposed a model of bilirubin circulation in the

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body using mathematical equations [4]. In another research in 2002, Seyfang et al presented an algorithm for diagnosis and treatment of jaundice in newborns using ASBRU language [5]. This algorithm presents how to diagnose and treat jaundice according to some laboratorial data including mother’s and child’s blood types.

American Academy of Pediatrics also suggested an algorithm for diagnosis and treatment of jaundice [6]. Another research in Switzerland shows the effect of season on the amounts of bilirubin in 5540 newborns cured by phototherapy [7]. According to this research, the maximum number of phototherapies occurred during May to August.

In 2001 Stevenson et al suggested the use of ETCOc[1], i.e., test of expiration carbon monoxide to force jaundice in newborns, considering release of carbon monoxide when heme changes to bilirubin [8]. They found that if total serum bilirubin is considered in addition to ETCOc in the first days after birth the risk of disease might be foreseen.

Khayati presented a procedure as a model for jaundice treatment using State Flow and Simulink toolboxes in MATLAB software by defining different states, relations between them, effects of different inputs and determining related outputs [9].

In 2003 Ahouraei et al tried to diagnose neonatal jaundice using an MLP neural network [10]. The neural network used in their study was standard feed forward network with two hidden layers, trained with back propagation.

III. Materials & Methods

A. Data Acquisition

Clinical data about newborns were collected by filling approved blank sheets from delivery occurrences during three months (since 12 April 2006 up to 15 June 2006) from two general hospitals (Baqiyatallah and Najmieh) in Tehran, Iran. Method of data acquisition was based on clinical data, physicians' prescriptions and questionnaire from the newborn’s family. This data include both newborns affected by jaundice and the healthy ones.

TABLE I
STATISTICAL INFORMATION ABOUT GATHERED DATABASE

		Quantity
Summary	Total research cases (healthy + jaundiced)	552
	Total jaundice cases of the research	391
Prediction Data	Total cases for prediction before delivery	515
	Total cases for prediction after delivery	333
Jaundice Classification Data	Pathologic	180
	Physiologic	161

At the end of data gathering period we had 552 records. Because of some missing values for each input feature and impossibility of complete follow-up we had to remove some incomplete record files. Of course because of different features for prediction and classification of jaundice, numbers of removals were different for each model. Some statistics about gathered data are presented in Table I.

There is a wide range of factors that affect neonatal bilirubin levels. Some of these factors have been identified only in large epidemiological studies and their clinical relevance is questionable, but there are some that have been shown repeatedly to have an important influence on total serum bilirubin (TSB) levels as a measure of jaundice severity [2]. Also some other factors have been reported as causes of pathologic jaundice in newborn infants.

Because of some restrictions in recording of above-mentioned factors we had to ignore some of them in our current study. Instead, some other factors considered which are listed hereinafter based on other studies, which have not been reported as most common factors, but have been mentioned in some cases [2].

B. Feature Selection

Features used for prediction before delivery include mother’s O blood group (being O blood group or not), mother’s having diabetes, mother’s having hypertension, fetus' gender, being the first child of family, siblings' jaundice background and mother’s age.

*Features used for prediction just after deliver*y include ABO incompatibility, Rh incompatibility, cesarean delivery, mother's regional (spinal) anesthesia for delivery, mother's using of oxytocin, mother's hypertension, mother's diabetes, infant's gender, being the first child, prematurity, siblings' jaundice background, mother's age, infant's weight, gestational age, and days of staying in hospital.

Features used for diagnosis of jaundice type (Physiologic/Pathologic) include jaundice persistence after first week, G6PD deficiency, total serum bilirubin (TSB), ABO incompatibility, appearance day of jaundice, prematurity and weight.

C. Multi Layer Perceptron (MLP)

MLP is one of the most frequently used neural network architectures, and it belongs to the class of supervised neural networks. It consists of a network of nodes arranged in layers. A typical MLP network consists of three or more layers of processing nodes: an input layer that receives external inputs, one or more hidden layers, and an output layer which produces the classification results (Fig. 1). Note that unlike other layers, no computation is involved in the input layer. The principle of the network is that when data are presented at the input layer, the network nodes perform calculations in the successive layers until an output value is obtained at each of the output nodes. This output signal should be able to indicate the appropriate class for the input data. That is, one can expect to have a high output value on the correct class node and low output values on all the rest.

A node in MLP can be modeled as an artificial neuron, which computes the weighted sum of the inputs at the presence of the bias, and passes this sum through the activation function. The whole process is defined as follows:

[1] End-tidal carbon monoxide (CO) for ambient CO

$$v_j = \sum_{i=1}^{p} w_{ji} x_i + \theta_j \quad (1)$$

$$y_j = f_j(v_j)$$

where v_j is the linear combination of inputs $x_1, x_2, ..., x_p$, θ_j is the bias, w_{ji} is the connection weight between the input x_i and the neuron *j*, and $f_j(\cdot)$ is the activation function of the *j*th neuron, and y_j is the output.

The sigmoid function is a common choice of the activation function, as defined in Eq. (2).

$$f(a) = \frac{1}{1+e^{-a}} \quad (2)$$

The bias term θ_j contributes to the left or right shift of the sigmoid activation function, depending on whether θ_j takes a positive or negative value.

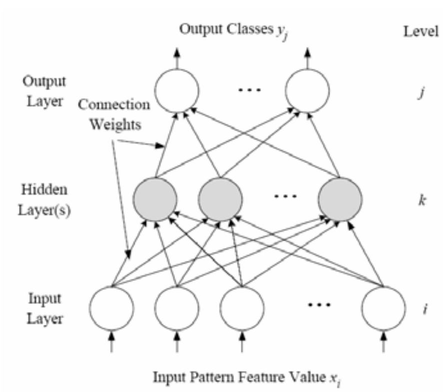

Fig. 1. Architecture of a multilayer perceptron network [11]

D. Applied MLP Based Models

The MLP models for all three cases (prediction before and after delivery and jaundice type classification) are designed using neural network toolbox of MATLAB software. To choose the best architecture of MLP neural network, it was trained and tested for different configurations. In fact different number of layers, neurons and training epochs and several activation functions such as linear and sigmoid were tested. In most cases resilient backpropagation (TRAINRP) was used as training function. In this algorithm only sign of derivative affects weight update and its magnitude does not have any effect on it. Learning rate was chosen 0.01 for all tries. The best results for each model will come in results section.

IV. Evaluation Method

To evaluate the performance of a classifier some indicating parameters are calculated from classifier results. One of the most common evaluators is called evaluation matrix. Four combinations of classifier output and desired output are possible for jaundice prediction, which are shown in Table IV. Based on these parameters some criteria are calculated which follow. In these formulae TP, FP, FN, and TN are number of occurrence of corresponding state [12]. A similar table can be given for evaluation of jaundice type classifier (pathologic/physiologic). In this case YES indicates presence of pathologic and NO indicates presence of physiologic jaundice type.

TABLE IV
EVALUATION MATRIX

		Jaundice Presence	
		YES	NO
Classifier Output	YES	True Positive (TP)	False Positive (FP)
	NO	False Negative (FN)	True Negative (TN)

• *Sensitivity (SE):* the probability that a test result is positive given the subject has the disease. In a suitable experiment the sensitivity can be estimated by: TP/(TP+FN)

• *Specificity (SP):* the probability that a test result is negative given a subject does not have the disease. In a suitable experiment the specificity can be estimated by: TN/(TN+FP)

• *Correct Classification (CC):* the probability that the test result reflects the true disease state. In a suitable experiment the probability of a correct classifier output is estimated as the proportion of cases for which the classifier output is correct: (TP+TN)/(TP+FP+TN+FN).

The performance of a classifier should, wherever possible, be expressed in terms of sensitivity, specificity and Correct Classification.

V. Results

Output neuron in this figure is 1 for jaundiced, and 0 for unjaundiced cases in prediction system. For jaundice type classification, output value of 1 means pathologic jaundice and 0 means physiologic. For each model we removed one input feature each time to clarify the effect of every feature on the classification result. For each model 70% of available data were used as training data.

Table V shows the results of prediction before and after delivery and jaundice type classification. The second column of table indicates the number of neurons of input, first and second hidden layers, respectively.

TABLE V
RESULTS OF APPLIED MODELS

Model	Nerurons	Train CC%	Train SE%	Train SP%	Test CC%	Test SE%	Test SP%
Prediction before	7,7,5	88.23	86.61	71.35	70.70	81.96	61.03
Prediction after	15,9,8	99.02	100	100	81.07	90.96	73.21
Jaundice Type	7,5,4	96.48	96.18	96.03	95.29	96.00	94.29

VI. DISCUSSION

Use of jaundice prediction and classification models will help to improve the health in society. This depends on modeling the complicated problems concerning jaundice in real situations. Although some directions and algorithms

presented by society of physicians do not show these complications but they appear at clinical diagnosis. Modeling of these cases succeeds only when we have enough data in hand along with views of expert physicians**.**

High percentage of jaundice (70.83) may due to Iranian race, then to the season of gathering data, which was in spring (April and June), and finally to the fact that almost all Iranian infants are breast-fed.

The different number of data entries used in each model is due to different number of missing data for each feature. Since number of features for prediction before and after delivery was 7 and 15, respectively the total missing data for after delivery is more than before delivery. In case of jaundice type classification, only jaundiced cases were used which were totally 391 cases of which 50 cases had missing data and were removed. As can be seen results of prediction before delivery are not very satisfactory. This is probably due to insufficient information for this prediction. However considering this fact that there is not any clear method about jaundice prediction up to now by physicians, even this level of prediction which is gained by neural network is at least a good step toward solving jaundice prediction problem. In case of prediction after delivery these results are more acceptable because some additional associated risk factors about the infant are available.

In case of jaundice type classification, physicians can almost easily reason it based on some laboratory measurements such as total serum bilirubin. It is a good idea to use an expert rule-based system such as fuzzy system on the basis of physicians' rules of thumb and then tune it to achieve the best classification result.

VII. Conclusion

This research was done after collection of a total of 552 medical records from infants born during 12 April up to 15 June 2006 in two general hospitals in Tehran, Iran. Because of some missing values for each input variable, impossibility of complete follow up and communication problems we had to remove some of incomplete record files. Of course because of different aspects for prediction and classification of jaundice, number of removals was different for each model. Finally 515, 333 and 341 files were used for jaundice prediction before delivery, after delivery and jaundice type classification, respectively.

This idea that we can predict risk of neonatal jaundice before and just after delivery was tried to be evaluated. For this purpose two neural networks are presented for prediction of the risk of jaundice before and just after delivery (in first 24 hours) of newborn. Also a neural network based system is presented to classify jaundice type into physiologic and pathologic. All three models are four layer MLP neural networks. The number of neurons in these three models is different due to different available input parameters for each model and is presented in relevant sections. . Because of different input parameters in these three models and missing data, three different numbers of record sets were used. To evaluate results of these models we used evaluation performance matrix criteria, which include percentage of accuracy (correct classification) (CC%), sensitivity (SE%), and specifity (SP%). The above mentioned criteria for jaundice prediction before delivery were approximately 71%, 82%, 61%, while for jaundice prediction after delivery were 81%, 91%, 73%, respectively. These results show that the proposed MLP based systems can achieve satisfying results for predicting risk of jaundice considering this fact that physicians do not have any estimation about probability of jaundice appearance. Also we achieved a very good result for jaundice type classification (95%, 96% and 94% for accuracy, sensitivity and specifity, respectively).

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